WPS 1437

POLICY RESEARCH WORKING PAPER 1437

Travel Mode Substitution in Saõ Paulo

Estimates and Implications for Air Pollution Control

Joffre Swait
Gunnar S. Eskeland

The study finds that households' choice of travel modes in Saõ Paulo is not very sensitive to pricing. So, subsidies to less polluting modes can hardly be justified on the basis that they would attract traffic from more polluting modes. Several caveats apply.

The World Bank
Policy Research Department
Public Economics Division
March 1995

Summary findings

How would travel demand in Saõ Paulo respond to demand management instruments? Could higher gasoline prices or lower metro fares (or changes in travel time) help reduce congestion or pollution?

Swait and Eskeland use cross-sectional variation from an urban travel survey to study the substitutability in demand between travel modes. The method assumes that the set of trips is given (that is, origin-destination pairs do not change). Choice of mode was found to be quite insensitive to changes: all elasticities were lower than 0.5 in absolute value, and most were close to zero. While the sensitivity of mode choice to relative travel times (that is, speeds) was somewhat greater than that to costs, the general finding is that mode choice is quite inflexible. So, subsidies to less polluting (less congesting) travel modes would not help much in attracting travelers from more polluting (more congesting) modes. (The same holds for subsidized means of making them run faster.)

But there are important limitations in the scope of the study. First, the study does not discuss optimal pricing. It merely examines the likely sign and magnitude of the links between pollution and policy parameters such as prices and travel speeds. Second, aggregate demand by mode could also depend on the city's shape and its travel intensity (the number, direction, and length of trips). For example, if a "city" stretches along a constructed metro line, the study would not capture such a phenomenon, since sensitive trip generation is excluded. These issues are not examined in the study.

This paper — a product of the Public Economics Division, Policy Research Department — is part of a larger effort in the department to study the use of fiscal instruments in environmental protection. The study was funded by the Bank's Research Support Budget under the research project "Pollution and the Choice of Economic Policy Instruments in Developing Countries" (RPO 676-48). Copies of the paper are available free from the World Bank, 1818 H Street NW, Washington, DC 20433. Please contact Carlina Jones, room N10-063, extension 37699 (45 pages). March 1995.

Travel Mode Substitution in São Paulo: Estimates and Implications for Air Pollution Control

by

Joffre Swait[1]
and
Gunnar S. Eskeland

World Bank, Policy Research Department,
Public Economics Division

1 Marketing Dept., College of Business Administration, University of Florida, Gainsville, FL 32606. The authors gratefully acknowledge the cooperation of the Companhia do Metropolitano de São Paulo - Metro; Mssrs. Rogério Belda and João Carlos Scatena, and to Jorge Rebelo of the World Bank, in making data available.

How would travel demand in São Paulo respond to demand management instruments such as changes in fares and travel times? The question is relevant from many perspectives - here the motivation is whether blunt instruments such as changes in gasoline prices or bus fares can assist in providing reductions in negative external effects such as pollution and congestion. The authors do not discuss how *optimal pricing rules* would depend on demand parameters (it depends on the available instruments, as well as on the objective function), but show how changes in emissions (including the sign) depend on demand parameters, inter alia.

This study uses an econometric technique to study the flexibility in mode choice. The data set is a travel survey of households from 1987, and cross-sectional variation is exploited to make inference about how flexible households are, given each trip's origin and destination.

Mode choice is found to be quite inflexible (but more sensitive to changes in travel times than to changes in fares and costs) - all elasticities are less than .5 in absolute value and most are near zero. This finding is generally in line with what is found in the literature on this topic. Thus, it would be hard to justify subsidies to the less polluting modes by referring to the traffic they attract from the more polluting ones.

The limitations in the study's scope should be recognized, however. Aggregate demand by mode could depend, in addition, on the number, direction and length of trips, on "city shape" (which may or may not be amenable to demand management) -- issues not examined in this study. As an example, if one has observed that a city "streches" along a newly constructed metro line, the study would not be able capture such a phenomenon, since it does not capture flexibility in trip generation.

1.0 INTRODUCTION

External effects are associated with total transport in a city, as well as with its distribution by transport mode and by details on how each of these modes are operated. With pollution generation, for instance, buses and cars can be made less polluting by technical modifications, but changes in travel demand patterns -- brought about by fiscal instruments such as taxes and subsidies -- can also provide cheap pollution reductions if consumers can easily adjust.[1]

One basic reason for considering fiscal instruments to reduce air pollution is that they circumvent the need for monitoring emission sources, without which one cannot implement first-best instruments such as emission taxes. Particularly in a developing country context, such monitoring can be quite expensive, if not impossible. Thus, it seems expedient to consider alternative means of control, such as taxation of fuels and/or vehicle ownership. Part of such a consideration will be to investigate whether demand for polluting goods and services is responsive to instruments such as taxes and subsidies. Such responsiveness determines the emission reductions that demand management instruments can provide. For instance, if intermodal substitution is low (as much of the literature indicates), then subsidies to public transport can hardly be supported on the basis that they reduce private vehicle use, accidents and pollution. On the other hand, if demand for bus services is elastic, then subsidies to such services can reduce private car traffic if much of the generated demand for bus trips are trips that would otherwise have been made by car[2]. However, for bus subsidies to reduce pollution, not only must intermodal substitution elasticities be high, but buses must also be "cleaner" than cars (say, per person kilometer). Another reason for studying the

[1] The reader is directed to Jimenez and Eskeland (1990) and Eskeland (1994) for a discussion of the motivation for using fiscal instruments to achieve environmental protection.

[2] While we concentrate on relative prices *between* modes, for which taxation of the more polluting modes is similar to subsidization of the cleaner ones (shifting modal shares), we should keep in mind that the former would simultaneously reduce demand for transport in general, while the latter would increase it. This study is on modal distribution alone, and thus does not highlight this distinction.

sensitivity of demand for market goods is that these determine the pollution consequences of policy changes that are implemented for reasons other than environmental protection.

It can be useful, in the following, to have in mind a simple model of the generation of pollution from urban transport. Let $E=e_i x_i$ be a measure of of emissions (say, grams of particulates), where e_i are emissions per passenger kilometer x_i for travel mode i, and let $x_i(p_1,t_1,..,p_m,t_m,I)$ be the demand for travel mode i, given prices $p_1,..,p_m$, travel times $t_1,..,t_m$, and income I.

If the pollution control agency can induce a change in the consumer price of mode j, the marginal effect on total emissions will be[3]:

$$\frac{\partial E}{\partial p_j} = \Sigma_i\left(e_i \frac{\partial x_i}{\partial p_j} + \frac{\partial e_i}{\partial p_j} x_i\right).$$

Assuming that the latter element is zero[4], the elasticity of emissions with respect to p_j will be the weighted sum of the demand elasticities, where the weights are each mode's share in total emissions:

$$\frac{\partial E}{\partial p_j}\frac{p_j}{E} = \Sigma_i \frac{e_i x_i}{E}\eta_{ij}$$

While more involved models are necessary to assess the welfare costs (and the attractiveness) of changing fares, prices and travel times, these expressions are useful in themselves to assess whether a policy change can deliver emission reductions. For instance, a

[3] The same calculus will hold if the agency can make the mode faster, or more/less attractive by other means.

[4] We have thus assumed that marginal emissions, in the context of changes in consumer prices or travel times, equal average emissions. This will often be a fair approximation. Important exceptions are: i) if cars and car trips are not all equally polluting, and the more polluting respond more to the price increases (i.e. older cars get scrapped); ii) if speeds are not held constant, remaining traffic can move at speeds that are less polluting; iii) if vehicle occupancy rates change, given that the chosen denominator in a demand focused study will be emissions per person-kilometer, or person-trip.

reduced fare for a "cleaner" mode, c, can deliver emission reductions (assuming the emission factor for the public mode, $e_c>0$), only if the emission elasticity with respect to p_c is positive. With two modes, the cleaner and "other", the absolute value of the own price elasticity for the cleaner must not exceed:

$$|\eta_{cc}| \leq \frac{e_o x_o}{e_c x_c} \eta_{oc}$$

The intuition is very basic: The own price elasticity of the mode which subsidy is being increased must not be "too large" compared to the cross price elasticities - otherwise the attracted traffic will to a great extent be additional, rather than attracted from the more polluting mode(s). If the two modes play the same role in emissions ($e_c x_c = e_o x_o$, so that the cleaner mode has a proportionately larger market share), then the cross price elasticity has to be greater than the own price elasticity. We shall revert to some simple calculations like these when the demand parameters have been established.

There are other studies and other methodologies that investigate the determinants and responsiveness of aggregate demand, such as studies of vehicle ownership and gasoline demand.[5] These studies leave two gaps in empirical knowledge which motivate the use of household level data from travel surveys. One is that they rarely allow a focus on all the travel demand modes, let alone the substitutability among them. Another is that the analyst is barred from investigating other details of the choices involved. For instance, if a study based on aggregate demand data reveals that a *city* reduces its gasoline demand as a result of higher gasoline prices, it may be unable to reveal the extent to which this is: i) because trips become shorter (people and employers could move closer to each other, or establish pairs in shorter distances, without moving, or discretionary trips could become shorter); ii) because the number of trips is reduced; iii) because cars become more fuel efficient, or, eventually; iv)

[5]Examples are: Eskeland and Feyzioglu, 1994 (Vehicle ownership and gasoline demand), Pindyck, 1979 (gasoline demand), Krupnick, 1992, Sterner, 1990 and Oum et al., 1990 (literature reviews).

because mode choice is affected, and trips are rather made by foot or bicycle, as an auto passenger, or by public transport modes.

Mode choice models, like the present one, use survey data to investigate the role of iv). Thus, the present model asks: *for a specific set of trips (i.e. each trip is specified in terms of person, origin and destination), by how much is the choice of travel mode affected by variables such as time and money spent on each mode, or by an increase in the income level?*

We use data on auto ownership and trip-making from Sao Paulo, Brazil, collected during the 1987-Origin-Destination Home Interview Survey by the Companhia do Metropolitano de Sao Paulo - Metro. With these data, encompassing a subsample of 1,500 households, we estimate work and non-work home-based Muntinomial Logit (MNL) mode choice models. These are then nested with a MNL auto ownership model, to capture the effect that changes in the transport system (e.g. travel cost changes due to a gasoline tax) would have upon the propensity to own an automobile. The proposed model structure reflects a utility-maximization framework within which the impact of certain fiscal policies on mode choice, auto usage and ownership can be examined.

It should be noted that the available data are cross-sectional in nature. Hence, prices are fixed in the sample; the only variations in prices, travel times and incomes that can be observed are those that vary due to other characteristics (e.g. distances) that are different from one observation to another. Despite the shortcoming, the model system developed is typical of what can be done econometrically with the usual transportation data sources available today, whether in developing or developed countries.

The remainder of the report is organized as follows:

1. a brief review of the literature on auto ownership and mode choice modelling is presented;
2. we then present an overview of the estimated model system;
3. this is followed by a presentation of the estimation results;

4. the estimated models are used to evaluate the impact of policy instruments such as taxes and subsidies, to be used in analysis of policy objectives such as reduced pollution;
5. we conclude with a discussion about the results of the research and their implications for future work.

2.0 LITERATURE REVIEW

We present in this section a brief literature review covering transportation and economic modeling efforts aimed at evaluating the impact of fiscal policies on the ownership and use of the automobile, with special emphasis on LDCs.

There is a well-developed US literature on automobile ownership, but its emphasis is on the vehicle-type and brand choice. It is a very sophisticated literature, but many of the problems it deals with (e.g., multiple-vehicle households; see Mannering, 1987) may be peculiar to developed nations, if not almost strictly to the US. There is also much interest in the timing of the vehicle replacement decision. Much effort is also expended on econometric issues that arise from the use of panel (i.e., longitudinal) data, something virtually unknown in LDCs (e.g., see Golob, 1990; van Wissen and Golob, 1992).

Train's (1986) work on auto ownership and utilization in California is of some relevance. He models the joint decision of auto ownership and utilization in a consistent demand system. The discrete dependent variable is the choice of the number of vehicles to own by make/model/vintage, and the continuous dependent variable is the annual VMT (vehicle miles traveled) for each vehicle. This is at a far greater level of detail than available in the São Paulo data, which has only information on the number of vehicles owned. Train's models were subsequently utilized by the California Energy Commission to study gasoline consumption and pollutant generation in the state. More recently, these models have been updated and recalibrated with new data. (These results are as yet unpublished, however.)

Stanovnik (1990) compared the effect of income on auto ownership in several Yugoslavian republics. Probit models, using the single variable income, are fit to individual household observations. Despite the parsimony of the specification, it is shown that income is a *very* important determinant of auto ownership in that country. This is also certainly expected to be the case in Brazil, as borne out by previous work of Swait (1981, 1985).

Brownstone and Golob (1992) calibrated ordered p.obit models of choice between driving and ridesharing for work trips in Southern California. Their models show that a combination of incentives could potentially increase ride-sharing by up to 18%, which in turn has implications for air pollution control.

3.0 MODEL STRUCTURE

3.1 Introduction

To meet the objective of producing a tool that permits the examination of the impact of travel demand management options (e.g., gaso'ine tax, automobile ownership tax, public transport subsidies) on the production of pollutants by personal vehicle travel, we have developed a Nested Multinomial Logit (NMNL; see McFadden 1981, Ben-Akiva and Lerman 1985 for descriptions of this model form) simultaneous choice model of

- auto ownership state (none versus one or more automobiles);
- work home-based mode choice;
- non-work home-based mode choice.

In the following pages we describe the rationale behind the model structure.

3.2 The Automobile Ownership Model

Auto ownership in a developing country such as Brazil is influenced by a number of factors, but most importantly by simple economic considerations: is vehicle ownership affordable to a given household? The decision of whether or not to own an automobile is in large part a function of a household's socioeconomic status, proxied in large part by its income.

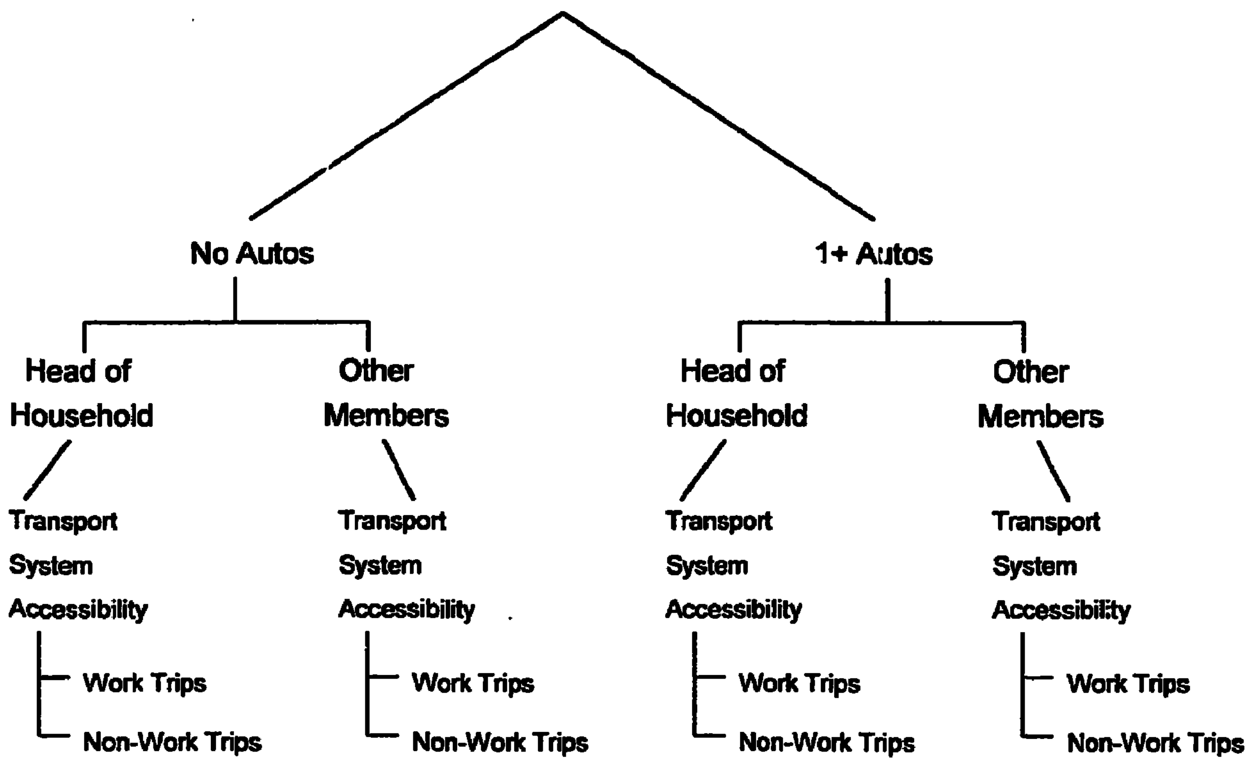
Nonetheless, other factors do influence auto ownership:

- the *automobile is a status symbol for Brazilians*, many of whom are willing to undertake the cost of vehicle ownership while controlling utilization (so as to minimize operating costs). During the late 1970's and early 80's, when Brazil operated under severe fuel shortages and was putting into operation the fuel alcohol program, the rate of increase in the vehicle fleet did not appreciably drop, but utilization of the fleet certainly did. This lends some credence to the hypothesis that the demand for automobiles is somewhat insensitive to ownership and operating costs, insofar as the car is a status symbol;

- it is our personal experience that Brazilians buy great quantities of vehicles through financing or consortia (the latter are temporarily convened purchasing cooperatives for durable goods, operating long enough for a group of 100 individuals, say, to acquire automobiles at the rate of two or three a month); this causes the *income constraint on vehicle purchase to be expressed (and perceived) in terms of the affordability of monthly payments rather than long-term tradeoffs between vehicle ownership and other options* (e.g., home ownership, education);
- *transportation system accessibility* is also a factor to be considered in the modeling of auto ownership, since it simultaneously describes the financial impact that vehicle use has on auto ownership and the benefits derived from having an automobile available. It is an empirical question, of course, as to whether the accessibility experienced by the various members of a household (i.e. heads of household as compared to other workers) are equally important in affecting the demand for automobiles, or whether different trip purposes (e.g. work vs. non-work trips) affect the demand differentially.

To account for all these factors, we have proposed the overall model structure shown in Figure 1. The decision tree depicted in the figure reflects the assumption that automobile ownership is a higher-level decision than that of the specific modes chosen for work and non-work trips by different members (e.g. the head of household, secondary workers, etc.) of a household. As such, the decision to own a vehicle is determined (in part) by the transportation needs of household members, represented in Figure 1 through the lower-level decisions of which mode to use for work and non-work trips. Other determinants of ownership will be income, status-fulfillment needs and so forth, as discussed before. Hence,

Figure 1 - Overall Structure of the Auto Ownership Model



we define the indirect utility function $U_{n,1+}$, the utility of automobile ownership for household n, to be given by

$$\begin{aligned} U_{n,1+} &= V_{n,1+} + \varepsilon_{n,1+} \\ &= \beta_{1+} + \beta_Y \ln Y_n + \beta_{HS} HS_n + \beta_C C_n + \beta_O O_n + \gamma L_n + \\ &\quad \delta TA_{n,1+} + \varepsilon_{n,1+} \end{aligned} \tag{1}$$

where

$V_{n,1+}$ $= \beta_{1+} + \beta_Y \ln Y_n + \beta_{HS} HS_n + \beta_C C_n + \beta_O O_n + \gamma L_n + \delta TA_{n,1+}$ is the deterministic (or systematic) component of the utility function;

$\varepsilon_{n,1+}$ is an error term, the characteristics of which are to be specified;

Y_n is the income for household n, included in the logarithmic form;

HS_n is equal to 1 if the head of household has a high school education or less, zero otherwise;

C_n is equal to one if the head of household has completed a college-level education, zero otherwise;

O_n is equal to one if the household owns its home, zero otherwise;

L_n is a vector of 15 residential location dummies, representing a 16 macrozone division of the São Paulo urban area;

$TA_{n,1+}$ $= (TA^{h,w}_{n,1+}, TA^{h,nw}_{n,1+}, TA^{o,w}_{n,1+}, TA^{o,nw}_{n,1+})$, represents the impact of the transport system on the demand for automobiles via the accessibility afforded to the head of household versus all other members, for work and non-work trips. It has elements $TA^{rs}_{n,a}$, which are the transport system accessibility for an individual of type r (head of household, other members) from household n for trip purpose s (work, non-work), when the household's automobile holdings are a vehicles (a=0, 1+); and

$\beta_{1+}, \beta_Y, \beta_{HS}, \beta_C, \beta_O, \gamma, \delta$ are unknown parameters to be estimated from data.

The corresponding utility of not owning a vehicle is given by the following expression:

$$U_{n,0} = V_{n,0} + \varepsilon_{n,0} = \delta TA_{n,0} + \varepsilon_{n,0} \quad . \tag{2}$$

Because of identification restrictions,[6] the utility of zero vehicles has only the transport accessibility vector $TA_{n,0}$[7] and the stochastic term.

If it is assumed that $\varepsilon_{n,0}$ and $\varepsilon_{n,1+}$ are identically and independently Gumbel distributed, the probability that a utility-maximizing household owns an automobile is given by the binary logit model

$$P_{n,1+} = \frac{\exp[V_{n,1+}]}{\exp[V_{n,0}] + \exp[V_{n,1+}]} = \frac{1}{1 + \exp[-(V_{n,1+} - V_{n,0})]} \ , \tag{3}$$

[6]In discrete choice models of the type estimated in this research, it is not possible to identify the effect of socio-demographic variables on all the alternatives (in this case, both 0 and 1+ automobiles). Instead, one of the alternatives must be used as a base (implicitly setting the corresponding parameter to zero) and the *relative* effects of the socio-demographics on the remaining alternatives can then be estimated.

[7]The elements of the TA vector vary depending upon the alternative, hence it is possible to identify the effect of transport accessibility on both alternatives 0 and 1+ automobiles.

where $V_{n,1+}$ and $V_{n,0}$ are the deterministic components of utility functions (1) and (2), respectively.

We now explain more fully how the impact of changes in the transport system will be reflected in model (3). McFadden (1981) and Ben-Akiva and Lerman (1985, chapter 10) explain that a measure of transport system accessibility that is consistent with utility maximizing behavior in a hierarchical decision structure such as shown in Figure 1 is

$$TA_{n,a}^{rs} = \ln\left(\sum_{j \in C_{n,a}^{rs}} \exp(V_{nj}^{rs})\right) \tag{4}$$

termed the "logsum" for obvious reasons. To define the terms in (4), $TA_{n,a}^{rs}$ is the transport system accessibility for an individual of type r (head of household, other members) from household n for trip purpose s (work, non-work), when the household's automobile holdings are a vehicles (a=0, 1+). The term V_{nj}^{rs} is the systematic utility of choosing transport mode j from among the available set C_{nj}^{rs}, for person type r and trip purpose s. These modal choice utilities must be estimated from appropriate models to permit the evaluation of (4). We shall return to this subject subsequently.

As a measure of transport accessibility, the logsum has two interesting properties:

- it is monotonically increasing with respect to choice set size; and
- it is monotonically increasing with respect to the systematic modal utilities.

Hence, adding an alternative to the choice set of the lower level decision *cannot* decrease the utility of auto ownership at the higher level; similarly, improving the utility of the auto drive mode (e.g. by decreasing automobile operating costs) cannot decrease the utility of auto ownership.

In addition, Ben-Akiva and Lerman (1985) show that the logsum is actually the expectation of the maximum of Gumbel-distributed variates. Hence, we can interpret the differences in transport accessibility afforded by different levels of automobile ownership, implicit in expression (3), to be the difference between the maximum utility yielded by the lower-level modal choice decision (see Figure 1), given no automobile in the household, and the maximum utility yielded by the lower-level modal choice decision when the household owns at least one automobile. To see this more clearly, isolate the terms in (3) containing only the transport accessibility variables, and note that

$$P_{n,1+} = \frac{1}{1+\exp[\ldots+\delta(TA_{n,0}-TA_{n,1+})]} \quad . \tag{5}$$

Thus, all other things being equal, as the transport system accessibility for a household increases because of owning an automobile, the probability of its owning an automobile increases (it is expected that $\delta > 0$). Conversely, as the costs of vehicle operation increase (making it more expensive to use the automobile for work and non-work trips), one would expect the utility of auto-related modes to decrease, decreasing the accessibility variables, therefore leading to a smaller likelihood of owning a vehicle.

An examination of the 1987 São Paulo O/D survey subsample of 1500 households available for this analysis shows the distribution of auto ownership seen in Table 1. We have only modeled the frequency of owning one or more vehicles among São Paulo households, aggregating the two higher categories in Table 1. The reason for this is that the motivation for ownership of the second (or higher) vehicle can be quite different from that for the first automobile. The data we are utilizing, since it was not collected with the explicit motivation of modeling auto ownership, does not provide much basis for detailing auto ownership level beyond the first. All possible households are utilized, but as has been made clear before, we are modeling the ownership of *one or more* vehicles.

Before continuing to the mode choice models, we wish to also make clear that in our modeling system we are maintaining residential and employment locations fixed. This precludes modeling the effect of transport system accessibility (specifically, as impacted by the fiscal policies we consider) on these longer-term decisions.

Table 1 - Sample Automobile Ownership Distribution

Number of Vehicles Owned by Household	% of Households (Unweighted)
0	52.9
1	35.3
2+	11.8

3.3 The Mode Choice Models

In the exposition about the structure of the auto ownership model, it was made clear that the estimation of work and non-work mode choice models would be required. These models are to be used to estimate the logsum variables in model (3), which reflect the effect that changes in the transport system (inasmuch as that system can be expressed through the mode choice models) might have on auto ownership. In this section we discuss the specification of the mode choice models.

First, however, we wish to make some comments concerning the definition of trips to be modeled. The 1,500 household sample of trips includes a total of 9,331 trip records. These are distributed as shown in Table 2. To capture the impact of transportation system accessibility on auto ownership, we have calibrated mode choice models for work and non-work (recreation, personal business, health, shopping) trip purposes. In addition, we have used only home-based trips (i.e., trips that originate at or are destined to the trip-maker's residence) in the proposed model system. There are two reasons for this:

- first, and foremost, the modeling of non-home-based trips (e.g. the trip taken from work to a supermarket before heading home from work) is very complex and actually requires modeling of *activity patterns* rather than single trips;

Table 2 - Sample Trip Purpose Distribution

Trip Purpose	Number of Trips	% of Trips (Unweighted)
Work, Home-Based	4045	43.4
Non-Work, Home-Based	2149	23.0
School, Home-Based	1621	17.4
All Non-Home-Based	1516	16.2
Total Trips	9331	100.0

- as shown in Table 2, they comprise a relatively small portion of the total trips (16.2%), so the omission is not felt to be a serious one.

We have omitted from the model system all non-home-based trips as well as all home-based school trips.[8] This implies that 66.4% of the trips made in São Paulo are actually included in the model system.

3.3.1 The Home-Based Work Trip Mode Choice Model

A little over 40% of all trips in São Paulo are estimated to be work home-based, which makes it the single largest trip purpose. The following eight modes are present in the data:

1. Auto Drive
2. Auto Passenger
3. Bus/Trolleybus
4. Metro/Suburban Train

[8]The omission of home-based school trips from the scope of our modeling work is a relatively arbitrary decision, mainly guided by the significant amount of work involved in such an effort. Specifically, one would have to develop models of trip-making behavior for the elementary, secondary and university levels (for an example of such models, see Swait et al., 1984). We also felt that the addition of this trip motive would not introduce substantive differences in the policy analyses undertaken.

Table 3 - Estimation Sample Distribution of Home-Based Work Trip Mode Choice

Mode	% of Trips (Unweighted)
Auto Drive	20.4
Auto Passenger	4.5
Bus/Trolleybus	40.6
Metro/Suburban Train	18.6
Employer-Sponsored Bus	5.5
Bicycle or Walk	9.0
Motorcycle	1.6

5. Employer-Sponsored Bus
6. Bicycle/Walk
7. Motorcycle
8. Taxi

However, because of extremely low choice frequencies in the available data, the taxi mode had to be dropped from the analysis.[9]

Table 3 shows the distribution of work trips by mode in the estimation data set. Approximately 26.5% of all work trips are made by motorized private modes (auto drive, auto passenger and motorcycle), 5.5% are made by employer-sponsored bus (which is intermediate between the private and public transport modes), 9.0% are bicycle or walk trips, and the remaining 59% are made by the public modes (bus and metro/suburban train).

The specification of modal utilities is hypothesized to depend upon the following factors:

1. **Travel Time:** Utilizing network-based estimates, provided by the Metro company, for automobile, bus and metro travel times, we have used auto travel times for the auto drive and auto passenger modes. In the case of motorcycle, we have assumed that actual travel time is proportional to auto travel time. The travel

[9]Extremely low aggregate choice frequencies for an alternative generally create empirical (as opposed to theoretical) parameter identification problems that can only be resolved by obtaining more data, or barring that option, omitting the alternative.

time for the walk/bicycle mode is assumed to be proportional to interzonal network distance. In the case of employer-sponsored bus, the actual travel time is assumed to be proportional to private automobile travel time. And finally, the travel times provided for bus and metro/train were utilized for those modes. For notational purposes, we denote the travel time for mode j for individual k as t_{kj}.

2. **Travel Cost:** Metro provided an average automobile ownership and operating cost per km, which is assumed to hold for the auto drive and passenger modes. It is assumed that the ownership and operating cost of a motorcycle is proportional to the automobile cost. At the time of the survey, bus fares were an average of US$0.25 and metro/train fares US$0.22. Because we did not have available information on number of transfers required between zone pairs for bus and metro trips, we have the situation of an invariant mode price. This forced us to utilize a specification of travel cost (c_{kj} is the notation for the travel cost for individual k, mode j, from home to work or vice-versa) divided by household income (denoted by Y_n, which is the nth household's income) to permit identification of a travel cost impedance for the bus and metro/train modes.[10] To maintain consistency, this variable was used for all modes.[11]

3. **Socio-demographic Factors:** In addition to the travel impedance measures considered above, it was hypothesized that modal utility depends upon the educational level of the head of household n (HS_n and C_n, previously defined), home ownership (O_n, also previously defined), gender of the head of household (G_n, equal to 1 if male, 0 otherwise), whether the traveler is head of household (HH_n, equal to 1 if traveler is head of household, 0 otherwise),

[10]The only alternative to this would be to exclude the cost variables for these two mode from their respective utility functions, which is not a very palatable option.

[11]This specification reflects the assumption that the marginal disutility of travel cost decreases with increasing income.

whether the occupation of the head of household is an industrial laborer (IL_n equal to 1 if head of household is an industrial laborer, 0 otherwise) and whether the occupation of the head of household is in the service industry (SI_n equal to 1 if the head of household holds a service industry job, 0 otherwise). However, it was felt that the effect of these sources of consumer heterogeneity should be permitted to differ between private modes (auto drive, auto passenger and bicycle/walk), non-private modes (bus, metro/train and employer bus) and a base mode (arbitrarily taken to be the motorcycle).[12]

On the basis of these factors, we define a linear-in-the-parameters modal utility for work trips as

$$U^w_{k(n),j} = V^w_{k(n),j} + \varepsilon^w_{k(n),j} \quad , \tag{6}$$

where $V^w_{k(n),j}$ is the systematic utility for individual k's (who belongs to household n) work trips by mode j, and the other term is the stochastic component. If the error terms are IID Gumbel, the choice probability is

$$P^w_{k(n),j} = \frac{\exp(V^w_{k(n),j})}{\sum_{i \in C^w_{k(n),j}} \exp(V^w_{k(n),i})} \quad . \tag{7}$$

Note that the natural logarithm of the denominator of (7) is actually the work trip accessibility measure defined in expression (4). Though we do not make it explicit in (7), because of the inclusion of the head-of-household dummy variable in the systematic utility we are able to differentiate between the work trips of the heads of household and other household members.

The symbol $C^w_{k(n),j}$ in (7) represents the set of modal alternatives available to individual k of household n for work trips (i.e. the choice set). When estimating discrete choice models based on revealed preference data, it is necessary to specify the rules whereby the choice set is constructed. In the present case, the following rules were applied:

[12]Another hypothesis would be to permit these parameters to vary from mode to mode, but it is often the case that identification problems occur, so this compromise approach was adopted here.

1. the auto drive and motorcycle modes were only permitted if the household owned at least one vehicle and the traveler was at least 18 years of age (to approximate the availability of a driver's license, which was unavailable in the data); note, however, that the auto passenger mode was made available irrespective of household auto ownership level, based on the prior experience of Swait and Ben-Akiva (1987) with the 1977 São Paulo O/D survey data;
2. for all modes, the network impedance matrix had to indicate that a link between the origin and destination zones was feasible.

3.3.2 The Home-Based, Nonwork Trip Mode Choice Model

The second group of trip purposes that we have modeled is commonly known in transport parlance as home-based nonwork trips. In our data, the actual trip purposes covered are recreation, personal business, health and shopping. Hence, this group of trips covers a more discretionary type of travel that has as its origin or destination the home.

Table 4 shows the modal split for the home-based work trips available for estimation. Only five modes (auto drive, auto passenger, bus, metro/train and bicycle/walk) were observed in the data, hence we are limited to modeling these alternatives. Note that in contrast to the work trips discussed above, auto passenger is far more utilized for non-work trips, as would be expected.

The same linear-in-the-parameters specification was used for the systematic component of the modal utility for nonwork trips (denoted $V^{nw}_{k(n),j}$) as described for work trips in Section 3.3.1. The choice set formation rules were also the same. The specification of the stochastic component is also IID Gumbel, so that the probability for nonwork home-based mode choice is also a multinomial logit model:

$$P^{nw}_{k(n),j} = \frac{\exp(V^{nw}_{k(n),j})}{\sum_{i \in C^{nw}_{k(n),l}} \exp(V^{nw}_{k(n),i})} \quad . \tag{8}$$

Table 4 - Estimation Sample Distribution of Home-Based Nonwork Trip Mode Choice

Mode	% of Trips (Unweighted)
Auto Drive	23.3
Auto Passenger	16.6
Bus/Trolleybus	37.9
Metro/Suburban Train	12.5
Bicycle or Walk	9.7

3.4 Built-in Assumptions and Restrictions of the Model System

Before proceeding to present the model estimation results, we now take a few moments and examine some of the built-in assumptions and restrictions embodied in the model system represented by expressions (3), (7) and (8) and depicted graphically in Figure 1.

1. Only home-based work and nonwork (recreation, personal business, health and shopping) trips are considered, which accounts for approximately two thirds of the trips in the São Paulo metropolitan area (as estimated with our sample data).
2. As stated before, the models assume that the residential and employment locations remain unchanged in the face of changes in the accessibility of the transport system (interpreted in the spirit of the accessibility variables defined in expression 4). That is to say, a consumer facing a work trip will respond to changes in the transport system by changing his or her mode of travel, not by moving residence to a more convenient location or changing to a more conveniently located job. The relaxation of these assumptions would require

the modeling of residential location and work trip distribution, both of which would require large-scale modeling efforts beyond the scope of the study and available data.

3. The models also assume that a consumer's discretionary travel behavior (i.e. nonwork trips) will be affected by transport system alterations only by changing mode utilization patterns. The modeling of the decisions to not make a discretionary trip or change its destination would require the development of trip generation and distribution models. The former are an especially daunting prospect since the prediction of the number of trips to be taken has always been a difficult task in transportation demand analysis.

4.0 MODEL ESTIMATION RESULTS

In this section we present the estimation results for the two mode choice models and the auto ownership model. However, we shall invert the order of presentation of the estimation results, with respect to the presentation of the model structure in Section 3.0. In essence, we shall be "ascending" the overall structure depicted in Figure 1.

4.1 The Work Mode Choice Model

Table 5 shows the maximum likelihood parameter estimates and their asymptotic t-statistics, based upon the estimation sample of 2,826 home-based work trips. On average, each trip had allocated to its choice set 4.9 alternatives.

The overall goodness of fit statistics are

$$\rho^2 = 1 - LL(\hat{\beta}) / LL(0) \tag{9}$$

and

$$\bar{\rho}^2 = 1 - [LL(\hat{\beta}) - K] / LL(0) \quad , \tag{10}$$

where $LL(\hat{\beta})$ is the sample log likelihood evaluated at the estimated parameters, LL(0) is the sample log likelihood at the naive equiprobability model, and K is the number of parameters in the model. As with R^2 in regression, these measures vary between 0 and 1. However, a good model can have values as low as on the order of 0.2-0.3. The second measure contains a degrees of freedom correction to promote parsimony in the model.

In the work trip mode choice model these goodness of fit measures are 0.429 and 0.422, respectively. These are quite high values, indicating the overall fit of the model is quite good. This is supported by the percent of trips correctly predicted by the model, which is approximately 55%; this value should be compared to the random choice model, which would correctly predict one seventh of the trips (i.e. the inverse of the number of modes), or about 15% (=1/7, where 7 is the total number of modes represented in the data).

Table 5 - Home-Based Work Trip Mode Choice Model Estimation Results

VARIABLE DESCRIPTIONS	FULL MODEL Parameter Estimates[1]
Alternative-Specific Constants	
Auto Drive	5.13 (7.4)
Auto Passenger	3.05 (4.3)
Bus	4.90 (7.2)
Metro/Train	5.67 (8.1)
Employer-Sponsored Bus	3.09 (4.4)
Bicycle/Walk	5.14 (7.4)
Motorcycle	-0-
Travel Times	
Auto Drive (min)	-0.0228 (-4.7)
Auto Passenger (min)	-0.0212 (-3.0)
Bus (min)	-0.0135 (-5.6)
Metro/Train (min)	-0.0209 (-8.0)
Employer-Sponsored Bus (min)	-0.0375 (-5.6)
Bicycle/Walk (km)	-0.3741 (-15.4)
Motorcycle (min)	-0.0539 (-4.1)
Travel Cost/Household Income (US$/ # of Minimum Salaries)	
Auto Drive	-0.1047 (-2.6)
Auto Passenger	-0.5896 (-5.2)
Bus	-0.0462 (-0.1)
Metro/Train	-5.4718 (-1.9)
Employer-Sponsored Bus	-0-
Bicycle/Walk	-0-
Motorcycle	-0.2268 (-1.3)
Socio-Demographic Effects (Auto Drive, Auto Passenger, Bicycle/Walk)	
Head of household has high school ed.	-0.786 (-1.9)
Head of household has college education	-0.921 (-2.0)
Household owns home	-1.204 (-2.8)
Traveler is male	-2.081 (-3.9)
Traveler is head of household	1.532 (4.3)
Occupation: Industry	-0.544 (-4.5)
Occupation: Services	-0.831 (-6.0)
Socio-Demographic Effects (Bus, Metro/Train, Employer Bus)	
Head of household has high school ed.	-0.953 (-2.3)
Head of household has college education	-1.755 (-3.8)
Household owns home	-0.972 (-2.3)
Traveler is male	-2.594 (-4.8)
Traveler is head of household	1.091 (3.1)
Log Likelihood	
At all parameters=0	-4298.8
At convergence	-2456.6
ρ^2	0.429
$\bar{\rho}^2$	0.422

1. Asymptotic t-statistics in parentheses.

Examining the estimated parameters, note that all the travel time coefficients are negative and highly significant. The travel cost coefficients are also negative, but some are not significantly different from zero. Specifically, the travel cost coefficient for the bus and motorcycle modes have small t-statistics. (The corresponding coefficients for employer-sponsored bus and bicycle/walk cannot be identified, of course, either because there is no direct cost to the consumer associated with the mode, as in the former mode, or because we have assumed that there are no out-of-pocket costs, as in the latter mode.)

With respect to the socio-demographic effects included in the model, we find that they are all significantly different from zero at approximately the 95% confidence level. Because MNL models are driven by *differences* in utilities, the impact of socio-demographic variables must be identified with respect to a base alternative (chosen to be the motorcycle mode in the present case). For example, to interpret the effect that being a head of household has on modal utilities, based on setting the referential that it has no effect on the utility of motorcycle, the parameter estimate indicates an increase of 1.532 utiles to the utility of auto drive, auto passenger and bicycle/walk compared to a non-head of household traveler, and an increase of 1.091 utiles to the utility of bus, metro/train and employer bus compared to a non-head of household traveler. Essentially, then, there is a higher propensity for heads of household to use the auto drive, auto passenger and bicycle/walk modes as compared to other household members, all other things being equal. Similar interpretation of differences indicates that the signs of the other socio-demographics are also reasonable.

4.2 The Nonwork Mode Choice Model

The 1,416 home-based nonwork trips available for estimation of this model were each allocated an average of 3.5 alternatives. The aggregate sample distribution of mode choice was previously given in Table 4.

The parameter estimates and goodness of fit statistics for the non work mode choice are presented in Table 6, under the rubric "FULL MODEL." In terms of overall goodness of fit, ρ^2 and its degree-of-freedom corrected counterpart have the values of 0.267 and 0.254, respectively. Though not as high as for the work trip model, these values nonetheless indicate a well-fitting model. The percent of correctly predicted mode choice decisions is about 50%, compared to the random choice model value of 20%.

Note that all travel time coefficients are negative and significantly different from zero. The travel cost coefficients for the auto drive and passenger modes are also negative and significantly different from zero, but the bus mode coefficient (despite being negative) is not significantly different from zero. The same outcome happened in the work trip model (see Table 5). However, the travel cost coefficient for the metro/train mode is slightly positive, though not significantly different from zero.

In general the socio-demographic variables are not as important to explaining variations in nonwork mode choice as in work mode choice behavior. However, the signs are in expected directions and the coefficients of head of household educational level, home ownership and gender of traveler are significantly different from zero.

Motivated by the undesirable positive sign of the Metro/Train travel cost coefficient, we have estimated a reduced model that eliminates that coefficient, which is termed the "REDUCED MODEL" in Table 6.[13] In addition, the reduced model has eliminated the educational level and home ownership variables from the bus and metro/train specifications. This elimination of four coefficients increases the log likelihood from -1262.4 to -1262.8. Hence, the chi-squared statistic to test the hypothesis that these coefficients are simultaneously equal to zero is $-2[-1262.8+1262.4]=0.8$, with 4 degrees of freedom. This test statistic is compared with the critical value of 9.49 at the 95% confidence level.

[13]We also attempted to estimate models that eliminated socio-demographic variables, in the hope that correlations between bus cost and certain consumer characteristics might explain the positive sign. The cost parameter continued to be non-significant and positive.

Table 6 - Home-Based Nonwork Trip Mode Choice Model Estimation Results

VARIABLE DESCRIPTIONS	FULL MODEL Parameter Estimates[1]	REDUCED MODEL Parameter Estimates[1]
Alternative-Specific Constants		
Auto Drive	-0.539 (-1.7)	-0.581 (-1.9)
Auto Passenger	-1.781 (-5.7)	-1.822 (-6.2)
Bus	-0.346 (-1.2)	-0.396 (-1.5)
Metro/Train	-0.322 (-0.9)	-0.354 (-1.1)
Bicycle/Walk	-0-	-0-
Travel Times		
Auto Drive (min)	-0.0161 (-2.4)	-0.0159 (-2.3)
Auto Passenger (min)	-0.0212 (-3.2)	-0.0210 (-3.2)
Bus (min)	-0.0090 (-2.6)	-0.0090 (-2.6)
Metro/Train (min)	-0.0112 (-2.9)	-0.0113 (-2.9)
Bicycle/Walk (km)	-0.3566 (-9.6)	-0.3567 (-9.7)
Travel Cost/Household Income (US$/# of Minimum Salaries)		
Auto Drive	-0.3268 (-3.7)	-0.3289 (-3.8)
Auto Passenger	-0.1886 (-3.0)	-0.1909 (-3.1)
Bus	-0.6212 (-0.6)	-0.7015 (-0.7)
Metro/Train	0.5268 (0.2)	-0-
Bicycle/Walk	-0-	-0-
Socio-Demographic Effects (Auto Drive, Auto Passenger, Bicycle/Walk)		
Head of household has high school ed.	0.436 (1.5)	0.599 (3.0)
Head of household has college education	1.154 (3.7)	1.084 (5.7)
Household owns home	0.542 (2.4)	0.595 (3.9)
Traveler is male	0.290 (1.2)	0.278 (1.1)
Traveler is head of household	0.128 (0.5)	0.135 (0.5)
Socio-Demographic Effects (Bus, Metro/Train)		
Head of household has high school ed.	-0.215 (-0.7)	-0-
Head of household has college education	0.096 (0.3)	-0-
Household owns home	-0.072 (-0.4)	-0-
Traveler is male	-0.446 (-1.9)	-0.458 (-2.0)
Traveler is head of household	0.327 (1.3)	0.335 (1.4)
Log Likelihood		
At all parameters=0	-1722.9	-1722.9
At convergence	-1262.4	-1262.8
ρ^2	0.267	0.267
$\bar{\rho}^2$	0.254	0.256

1. Asymptotic t-statistics in parentheses.

Therefore, we cannot reject the hypothesis that these coefficients are simultaneously equal to zero.

On a more practical level, it is somewhat unfortunate that the metro/train travel cost coefficient is essentially zero for this model. It is the probable result of the assumption of a single fare of $0.22 for any trip, which is the only thing that could be done since we have no information concerning the number of transfers necessary between an origin and a destination when the main mode is metro/train. In prior mode choice modeling exercises with São Paulo data (see, for example, Swait and Ben-Akiva, 1987), based on the 1977 home interview survey, a significant cost coefficient was found for the metro/train mode, though the travel time coefficient was not significantly different from zero. In this model, we have the exact opposite situation.

4.3 The Auto Ownership Choice Model

Of the 1,500 households available in the sample, 1,116 were actually usable for estimating the automobile ownership model due to missing data. To estimate the effect of transport system accessibility on the number of automobiles owned by a household, we used the work mode choice model and the reduced form nonwork mode choice model to estimate the transport accessibility variables (see expression 4) for heads of household and other household members, creating thus four logsum variables. However, since the logsums are sequentially estimated rather than simultaneously determined with the parameters of the auto ownership model, we have that the parameter estimates are consistent but not fully efficient (see McFadden, 1981, for a discussion of this point).

Table 7 presents the estimation results for the automobile ownership choice model. In terms of overall goodness of fit, the binary logit model denoted "FULL MODEL" in Table 7 has a ρ^2 value of 0.175, with a percent correctly predicted of 60% (compared to 50%

Table 7 - Automobile Ownership Model Estimation Results

VARIABLE DESCRIPTIONS	FULL MODEL Parameter Estimates[1]	REDUCED MODEL Parameter Estimates[1]
Alternative-Specific Constants		
Own 1+ Autos	-2.226 (-7.3)	-1.840 (-10.6)
Own 0 Autos	-0-	-0-
Socio-Demographic Effects (Alternative 1+)		
Natural Log of Household Income (Minimum Salaries)	0.2957 (4.5)	0.3061 (4.8)
Head of household has high school ed.	1.105 (5.4)	1.169 (6.0)
Head of household has college education	1.794 (7.0)	1.817 (7.7)
Household owns home	1.199 (7.9)	1.108 (7.7)
Residential Location Dummy Variables (Alternative 1+)		
Centro	0.259 (0.7)	-0-
Santana - N. Sra. do Ó	0.858 (2.2)	-0-
Tatuapé - Vila Prudente	0.562 (1.7)	-0-
Jabaquara - Ipirange	0.530 (1.4)	-0-
Jardins - Butantã	0.790 (1.6)	-0-
Lapa - Vila Madalena	0.990 (2.2)	-0-
Pirituba - Perus	0.381 (0.9)	-0-
Brasilandia - Tucuruvi	0.627 (1.7)	-0-
Guarulhos - Santa Isabel	0.158 (0.4)	-0-
Itaquera - Guaianazes	0.266 (0.8)	-0-
Mogi - Guararema	-0.160 (-0.4)	-0-
Mauá - Santo André	0.814 (2.3)	-0-
São Bernardo - Diadema	0.463 (1.2)	-0-
Santo Amaro - Campo Limpo	0.164 (0.5)	-0-
Taboão da Serra - Juquitiba	-0.185 (-0.5)	-0-
Osasco - Itapevi	-0-	-0-
Estimated Transport Accessibility (both alternatives 0 and 1+)		
Head of household - work trips	0.1975 (3.1)	0.0993 (2.1)
Head of household - nonwork trips	-0.0208 (-0.2)	-0-
Other members - work trips	-0.1510 (-1.8)	-0-
Other members - nonwork trips	-0.1153 (-0.9)	-0-
Log Likelihood		
At all parameters=0	-773.6	-773.6
At convergence	-638.1	-651.7
ρ^2	0.175	0.158
$\bar{\rho}^2$	0.144	0.149

1. Asymptotic t-statistics in parentheses.

for a random choice model). Thus, the twenty-four parameters in the full model are jointly significantly different from zero.

Household income is shown to have a very significant impact on automobile possession, as would be expected. Other wealth-related socio-demographic effects, such as the educational level of the head of household and the household's ownership of the home, are also strong explanatory variables. Most of the residential location dummies are not significantly different from zero, indicating that all other things having been accounted for, location does not have any impact on auto ownership. This is an interesting characteristic for the model to have, of course, since model inferences become less dependent upon the specific urban form and current population distribution.

The accessibility (logsum) variables, which capture the dependence of the auto ownership decision on the lower level transportation decisions of work and nonwork mode choice, yielded a mixed bag of results. The accessibility of the head of household for work trips is a strong explanatory variable in the auto ownership model, but none of the remaining logsums are significantly different from zero at the 95% significance level. In addition, except for the head of household work trip logsum, the accessibility variables have negative signs, which is counterintuitive.

Hence, the reduced form auto ownership model presented in the final column of Table 7 has eliminated all logsums except the head of household work trip accessibility, and has also removed all residential location dummies from the specification. Thus, the hypothesis that these 18 parameters are simultaneously zero can be tested with the chi-squared statistic of $-2[-651.7+638.1]=27.2$, which when compared to the critical value of 28.9 at the 95% confidence level, leads us to conclude that the full and reduced models are not significantly different from one another.

Our final specification for the auto ownership model shows the statistically significant influence that the accessibility afforded by an automobile to the head of a household for work travel has on the household's likelihood to possess one or more automobiles. Ben-Akiva and

Lerman (1985, Chapter 10) explain that as the coefficients of accessibility variables approach the value of 1.0, the greater the degree of jointness of the decisions being modelled; as the coefficients approach 0.0, the greater the degree of independence between the decisions. In the São Paulo auto ownership model we presented in Table 7, the work trip accessibility variable for the head of household has a coefficient of about 0.10. This indicates that the influence of head-of-household work trip accessibility, while statistically different from zero, is not among the most determining factors of automobile ownership. Previous experience indicates that household income (and more generally, wealth) should be the constraining factor for the automobile ownership decision.[14] Though somewhat surprising that the nonwork accessibility measures are not significant, this result is not wholly unexpected. In fact, it is quite consistent with usual Brazilian middle-class household structures, which tend to be single-worker units.

[14]This intuition is clearly borne out in the results of Section 5.0.

5.0 POLICY IMPLICATIONS OF THE MODEL SYSTEM

The integrated automobile ownership and mode choice models reported in the previous section have been used to evaluate the sensitivity of the three different decisions modelled (work mode choice, non-work mode choice and automobile ownership) to changes in different policy variables. Specifically, we have estimated population-level arc elasticities[15] of the response variables with respect to changes in two modal characteristics (travel time and travel cost) and to changes in household income. These variables, especially travel cost and household income, are of interest in this study because they would be directly impacted by such policies as fuel and car taxes, and the existence of faster or cheaper public transport modes potentially useful for controlling air pollution generated by automobile use.

We will first examine the lower-level (as in Figure 1) modal choice models, then the upper-level automobile ownership choice model.

5.1 The Work Mode Choice Model Results

Table 8 presents the own and cross arc elasticities of the work mode choice model with respect to changes in the travel times of the automobile, bus and metro/train systems.[16] The most sensitive mode is Metro/Train, which has an own time elasticity of -0.50; this is followed by Bus, with a corresponding value of -0.30, which is the same own elasticity as exhibited by the Auto Passenger mode; and finally, the smallest own elasticity is that of Auto Drive, with a value of -0.20. Some of these values are quite similar to those of Swait and Ben-Akiva (1987, Table 2a), who present São Paulo work trip arc elasticities (generated by

[15]The arc elasticities presented here were obtained by perturbing the independent variables by a 10% increase across the entire sample. Population-level estimates were obtained by sample enumeration using the limited sample we have available. These were then expanded to the total population by employing weighting factors provided by the Metro company. As presented, the arc elasticities have been normalized to be the percent change in the response due to a 1% change in the independent variable. The selection of a 10% perturbation to calculate the arc elasticities was purposefully small, so as to more closely approximate point elasticity estimates.

[16]Note that changes in automobile travel time affect both the Auto Drive and Auto Passenger modes.

Table 8 - Work Mode Choice Travel Time Arc Elasticities

	Response in Mode ...						
Change in Travel Time of ...	Auto Drive	Auto Passenge r	Bus	Metro/ Train	Employe r Bus	Bicycle/ Walk	Motor-cycle
Automobile	-0.20	-0.30	0.10	0.10	.20	0.10	-0.10
Bus	0.20	0.30	-0.30	0.20	0.40	0.20	0.30
Metro/Train	0.10	0.10	0.10	-0.50	0.10	0.00	0.10

100% perturbations of travel time, instead of the 10% perturbations used here) based on a mode choice model calibrated on 1977 data (as opposed to the data used in this study, which was collected 10 years later). Their values and ours are contrasted below:

	Work Trip Mode Choice Own Travel Time Arc Elasticity	
Mode	This Study	Swait and Ben-Akiva (1987)
Auto Drive	-0.20	-0.14
Auto Passenger	-0.30	-0.23
Bus	-0.30	-0.23
Metro/Train	-0.50	-0.02

Hence, the two sets of values are quite consistent with the exception of the rail mode; the present study has a *much* higher rail arc elasticity than found in Swait and Ben-Akiva.[17] For the purposes of this study, however, the automobile modes are of the greatest interest, so it is heartening to see the consistency between the two studies.

Table 9 shows the elasticities of the work trip mode choice model with respect to changes in travel cost. The bus mode is predicted to be inelastic, a direct result of its very small travel cost coefficient (see Table 5). The Metro/Train mode is also essentially inelastic

[17]However, it is noteworthy that our estimate is quite similar to that reported in that same study for a different model formulation (essentially a simultaneous captivity and choice model), as evident in their Table 2b, where the rail own elasticity is reported as being -0.30.

Table 9 - Work Mode Choice Travel Cost Arc Elasticities

Change in Travel Cost of ...	Response in Mode ...						
	Auto Drive	Auto Passenger	Bus	Metro/ Train	Employer Bus	Bicycle/ Walk	Motor-cycle
Automobile	0.00	-0.40	0.00	0.00	0.10	0.00	0.10
Bus	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Metro/Train	0.00	0.00	0.00	-0.05	0.01	0.00	0.00

because, despite its larger cost coefficient, only a small proportion of the population is actually impacted by changes in this mode.[18] Finally, the work mode choice model predicts that Auto Passenger has an own cost elasticity of -0.40 (these trips are predicted to transfer to the Employer Bus and Motorcycle modes), while the Auto Drive mode is unaffected by changes in travel cost.[19] The own travel cost elasticities from this and the Swait and Ben-Akiva (1987, Table 3a) study are again constrasted below.

Mode	Work Trip Mode Choice Own Travel Cost Arc Elasticity	
	This Study	Swait and Ben-Akiva (1987)
Auto Drive	0.00	-0.02
Auto Passenger	-0.40	-0.07
Bus	0.00	-0.14
Metro/Train	-0.05	-0.25

[18]Note that the elasticities refer to the change in population demand, given a change in the stimulus variable. Since few individuals are affected by the metro/train mode (i.e. not all origin/destination pairs are served by metro/train, even as a part of the total trip), changing its characteristics does not as widespread an impact as changing auto or bus characteristics.

[19]A possible reason for the larger impact of travel cost on the Auto Passenger mode, compared to the Auto Drive mode, is that we have assumed that passengers have an out-of-pocket cost proportional to that of the Auto Drive alternative. In reality, it is more likely that, within a household, there is no explicit cost associated with the passenger mode, so we may be overstating the sensitivity of the mode.

With respect to Auto Drive the two studies are in agreement as to the mode's inelasticity. Our model predicts that the Auto Passenger mode is more elastic than in the earlier study; conversely, we predict the Bus and Metro/Train modes to be less elastic than found in that study. Nonetheless, the conclusion that both studies point to a general insensitivity of work mode choice with respect to travel cost changes seems inescapable.

The final result to be presented for the work trip mode choice model is given in Table 10, which presents the modal arc elasticities with respect to household income. The results show that a 1% income increase most strongly affects the Auto Passenger and Motorcycle modes by drawing trips to them. The Metro/Train mode also gains some trips, but nothing significant. Bus, Employer Bus and Bicycle/Walk lose trips when household income increases. Interestingly, an income increase (at least of the 10% perturbation used here and given the existing income distribution in the sample) is predicted to have no effect on the Auto Drive mode. This means, of course, that the work trip mode choice model will exhibit a certain "stiffness" (or inertia, if you will) with respect to the impact of income changes on the Auto Drive mode, which is of special interest in this study.

Table 10 - Work Trip Mode Choice Household Income Arc Elasticity

Mode	Income Own Arc Elasticity
Auto Drive	0.00
Auto Passenger	0.40
Bus	-0.04
Metro/Train	0.03
Employer Bus	-0.10
Bicycle/Walk	-0.03
Motorcycle	0.10

5.2 The Nonwork Mode Choice Model Results

Tables 11, 12 and 13 present the nonwork mode choice arc elasticity results given by the reduced model of Table 6. The basic message of these tables is that nonwork mode choice is approximately as "stiff" as the work mode choice results discussed previously. Hence, we will simply point out a few differences between the two models:

- with respect to travel cost, nonwork trips by Auto Drive show some (small) elasticity, as compared to work trips, where the elasticity was zero;
- for nonwork trips by Auto Passenger the cost elasticity is about the same magnitude as the corresponding Auto Drive value, and only a quarter of the work trip Auto Passenger elasticity;
- the household income arc elasticity of the automobile modes are about 0.07 for nonwork trips, which contrasts with 0.00 and 0.40 for the Auto Drive and Auto Passenger modes for work trips.

Again, the essential conclusion of these results is that mode choice for non-work trips is quite inelastic with respect to travel time, travel cost and income changes, at least within the bounds of the perturbations tested and characteristics of the sample data available.

Table 11 - Nonwork Mode Choice Travel Time Arc Elasticities

	Response in Mode ...				
Change in Travel Time of ...	Auto Drive	Auto Passenger	Bus	Metro/ Train	Bicycle/ Walk
Automobile	-0.10	-0.30	0.10	0.10	0.10
Bus	0.09	0.15	-0.20	0.16	0.13
Metro/Train	0.02	0.03	0.04	-0.30	0.01

Table 12 - Nonwork Mode Choice Travel Cost Arc Elasticities

Change in Travel Cost of ...	Response in Mode ... Auto Drive	Auto Passenger	Bus	Metro/ Train	Bicycle/ Walk
Automobile	-0.09	-0.08	0.06	0.06	0.04
Bus	0.00	0.00	0.00	0.00	0.00
Metro/Train	0.00	0.00	0.00	0.00	0.00

Table 13 - Nonwork Trip Mode Choice Household Income Arc Elasticity

Mode	Income Own Arc Elasticity
Auto Drive	0.08
Auto Passenger	0.07
Bus	-0.05
Metro/Train	-0.06
Bicycle/Walk	0.00

5.3 The Automobile Ownership Choice Model Results

In this section we present the arc elasticities of the reduced form automobile ownership model (presented in Table 7) with respect to changes in travel time, travel cost and household income. Because of the inclusion of the transportation system accessibility variable for head of household work trips (see the discussion in section 3.2, expression (4)) in the automobile ownership model, *its arc elasticities include the effects of the perturbed independent variables in the lower-level model* (see Figure 1). Hence, the auto ownership model can be sensitive to changes in the transportation system characteristics, such as travel time or vehicle operating costs.

Table 14 shows the arc elasticities for the automobile ownership model. The results indicate that the ownership decision is basically unaffected by changes in travel time and travel cost in the range tested (10% perturbations). With respect to household income changes, the arc elasticity of automobile ownership is estimated at a low value of +0.10.

Table 14 - Automobile Ownership Arc Elasticities

Change ...	Arc Elasticity
Automobile Travel Time	-0.01
Bus Travel Time	0.01
Metro/Train Travel Time	0.00
Automobile Travel Cost	0.00
Bus Travel Cost	0.00
Metro/Train Travel Cost	0.00
Household Income	0.10

5.4 Effect on Emissions: Example Calculations

Analysis of demand management instruments to pursue emission reduction objectives requires more elements than those developed here. First, emissions of different pollutants should be weighted by their relative contribution to damages[20]. This amounts to obtaining a sensible, damage-weighted scalar for emissions (See equation 1.1, in which emissions is a scalar).

Secondly, since environmental damages are not of unique importance, one needs a model which allows analysis of the welfare costs of demand manipulation. The general

[20] Two possible approaches are to base these on a measure of relative non-compliance with standards for the various ambient air pollutants (See Weaver, World Bank, 1992), or on specific modelling of the airshed, physical effects, and valuation (Eskeland, World Bank, 1994).

recommendation in public finance is to tax emissions, rather than to tax or subsidize the more and less polluting goods and services. Thus, an argument for using taxes and subsidies on goods and services, whose impact on pollution is limited to the effects through changes in demand (as opposed to making each mode less polluting, per passenger kilometer), will usually rest on the assumption that such instruments require less costly monitoring and enforcement (See, for example, Devarajan and Eskeland, for an elaboration of this point).

A less demanding, though necessary intermediate question, is to what extent changes in relative prices or travel times can deliver emission reductions. To illustrate some calculations, we shall remain agnostic about damage-weighted emission factors, but use the demand elasticities estimated for work-trips (Tables 8 and 9), the modal shares for work trips (Table 3).

Table 9, with price (or cost) elasticities for the modal split of home-based work trips, gives immediate answers for subsidies to bus and metro/train. The metro/train own price elasticity is significantly different from zero, but small, at -.05, and the bus own price elasticity is not significantly different from zero. For both of these prices, however, estimated cross price elasticities are all zero. Since, in the spirit of equation 1.3, it would be positive cross price elasticities with "more polluting" modes that would drive a possible emission reduction, we can rule out that fare reductions could reduce emissions (subject to caveats in terms of the demand system that is estimated, of course).

Also, the demand system appears unable to deliver emission reductions in response to fuel price increases for automobiles, as own price as well as cross price elasticities are estimated to be equal to zero.

One might also consider making the public modes more attractive to consumers by other means than fare reductions, for instance by increasing their speeds. This could be implemented by administrative fiat (privileging lanes for buses), usually involving involving implicit "taxation" of other modes, or by explicit use of taxes and subsidies. In Table 9, we can see that the responsiveness of demand to travel times is greater than to costs (Table 8): For bus and metro/train travel times, own time elasticities are negative and cross-time elasticities are positive. For metro/train travel times, the own time elasticity is -.5, while cross time elasticities are .1. Thus, using equation 1.3, reductions in metro/train travel times can reduce emissions if $e_m x_m / e_o x_o < 5$, i.e. if total emissions from metro/train, relative to emissions of all other modes, is less than or equal to 5. In Table 3, we can see that the trip share of metro/rail is 18.6 percent. This means reductions in travel times for the metro/train would reduce emissions as long as the emission factor for the metro is not five times as great as the weighted average for other modes, which will surely be satisfied under all possible assumptions.

For a reduction in travel times for buses, ceteris paribus, calculations are as follows. The own time elasticity, -.3, applies to 40.6 percent of trips, while cross time elasticities of .2 apply to metro/train and walk/bicycle, with trip shares 18.6 and 9 percent, respectively. Assuming that metro/train and walk/bicycle can be considered not polluting, emission reductions will have to be delivered by the remaining 32 percent of trips, to which a cross time elasticity of .3 applies. The result is that travel time reductions for buses would deliver emission reductions if the emission factor for buses (per passenger kilometer) is smaller than or equal to 4/5 of the weighted average for other polluting modes, where other polluting are auto (drive and passenger): 24.9 percent, employer-sponsored bus: 5.5 percent, and motorcycle: 1.6 percent (thus, dominated by auto drive). According to the authors' experience, pollution coefficients for buses may or may not be lower than four fifths of what they are for cars, depending on the weighting of contaminants (buses more intense in particulates, cars more intense in ozone, carbon monoxide and lead), the characteristics of fleets and fuels, and load factors (passengers per vehicle).

Concluding, travel time reductions for metro/rail would reduce emissions, and for buses they *might* reduce emissions. Of course, travel time reductions are attractive to consumers for other reasons also, but can generally be delivered only at a cost[21]. Travel time reductions can therefore not be recommended without much more involved analysis.

[21] Krupnick (1993), making rough calculations, indicate that for projects producing travel time reductions, consumers' valuation of the reductions will dwarf the emission reductions.

Finally, a line of inquiry emphasized in this study was to investigate the role of endogenous car ownership in an economy where car ownership is not yet predominant among households. Rather rigid demand systems had been estimated in various countries, using methodoligies based on the assumption that car ownership is given. Thus, the possibility remained that a "hidden" responsiveness of demand systems could rest in endogenous car ownership, if car ownership appeared responsive to measures of relative travel times and costs. Table 14 demonstrates, however, that car ownership shows little responsiveness to any other variable than the households economic status. With the caveats necessary due to the data set and the methodology, therefore, it appears that the responsiveness to prices and travel times of car ownership does not add significant flexibility to an overall model of modal split for Sao Paulo.

6.0 CONCLUSIONS

Is urban travel demand amenable to demand management? This study provides a limited part of the answer, since it takes as given the specific trips (origin-destination pairs) that a sample of households undertake, when asking: how sensitive is the choice of travel mode to changes in exogenous variables such as each mode's travel cost and travel time?

The present research strongly supports previous modeling efforts with São Paulo travel data by showing that mode- and auto ownership decisions are relatively unresponsive to changes in relative travel costs, and also quite unresponsive to changes in relative travel times (e.g. Swait and Ben-Akiva, 1987, who used data collected 10 years before the data utilized in this modeling work). Considered together, the arc elasticities calculated using a multi-tiered demand system of models for work mode choice, non-work mode choice, and automobile ownership depict São Paulo travellers as quite inflexible in their mode choice. Own- and cross- elasticities with respect to travel time and costs are all less than 0.5 in absolute value, and most are near zero.

Evidence from another Brazilian city, Maceió, located in the under-developed northeast of Brazil, also shows that work mode choice (one of the components of behavior modelled here) is quite insensitive to travel time and income changes (see Swait and Ben-Akiva, 1986; Swait et al., 1984). Maceió is much poorer than São Paulo, so it is perhaps not surprising that the former's elasticities are even smaller than those reported here. These and other results mentioned above combine to suggest a limited substitutability among travel modes when trip origination and destination are predetermined. Thus, taxes and subsidies could not significantly reduce air pollution by removing riders from private vehicles to other, potentially less polluting modes, unless trip generation itself is responsive to such instruments.[22]

[22]Some stylized facts for individual interpretation: As recently reported in the Wall Street Journal, Brazilians are already subject to the highest automobile sales taxes in the world, yet ownership of an automobile still looms large as a worthy goal in consumers' minds (perhaps superseded only by the desire to own their own

There are several ways to read the findings from the present study, however. To see the study as confirming that urban travel demand is generally insensitive to parameters such as travel times and costs would be mistaken: the study finds that the choice of travel mode, given that a specific trip is undertaken, is unresponsive. Thus, total demand for trips may be sensitive to prices and travel times. Similarly, modal split may be responsive, if trip origins and destinations are not considered given, as in the present study. As an example, if one has observed the phenomenon that a city "stretches" its suburban expansion along a newly built metro line (possibly a phenomenon of responsive aggregate travel demand which includes a responsive modal split), then our study methodology would not be able to detect it, since it only investigates modal choice *given residential and employer locations*. To be specific, the study can say nothing about how responsive a "city" is, either in the total demand for travel or in its modal split. The study does find, however, that not much responsiveness is found in the choice of mode for given trips.

One policy implication is that it would be hard to justify subsidies to modes that require less road space or produce less pollution by referring to the benefits in terms of reduced congestion and pollution.

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home). Less stylized, but notable: During the second half of the 1970's, Brazil was implementing its renewable alcohol-fuel program; fuel (whether gasohol or pure alcohol) was expensive, scarce and rationed (e.g. gasoline stations within 50 kilometers of any urban area were closed from Friday evening through Monday morning). The study conducted by Swait and Ben-Akiva (1987) used survey data collected in 1977, and so was subject to these conditions. They report that 32% of the work trips were by the Auto Drive and Auto Passenger modes. Our sample, collected 10 years later, has 25% of work trips by those two modes (see Table 3). Thus, it appears as if these modes have reduced their shares, even though it may be that these two shares are quite close. With some, though limited per capita income growth, and with a removal of rationing mechanisms, one would expect increased use of auto modes. However, as the city and the sample has changed, it is difficult to analyze the causes of these differences, or even whether they are significant.

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